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Coupled Collaborative Filtering for Context-aware Recommendation

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Abstract

Context-aware features have been widely recognized as important factors in recommender systems. However, as a major technique in recommender systems, traditional Collaborative Filtering (CF) does not provide a straightforward way of integrating the context-aware information into personal recommendation. We propose a Coupled Collaborative Filtering (CCF) model to measure the contextual information and use it to improve recommendations. In the proposed approach, coupled similarity computation is designed to be calculated by inter-item, intra-context and inter-context interactions among item, user and context-ware factors. Experiments based on different types of CF models demonstrate the effectiveness of our design.

Introduction

Similarity computation among items or users is a critical step in CF algorithms (Su and Khoshgoftaar 2009). The original user preference or rating matrix ($L \times K$) in traditional similarity computation conventionally represents L different items rated by K different users. However, research on consumer behavior has shown that customer purchase behaviors are contingent on the context of decision making, such as time, location, and social networking (Adomavicius and Tuzhilin 2011)(Zheng et al. 2010). User preference or rating matrix can then be represented as a ($L \times K \times N$) extended preference cube tensor for the context-aware recommendation. The correlation between each pair of the user L and the item K preference is calculated with the N different contextual features.

In practice, the contextual information is usually linked to other entities in terms of coupled relationship and latent act on customer intention prediction (Cao 2013). These coupled relationships may not be sufficiently utilized to consider only users, items and locations independently when recommending items to users under certain circumstances. For example, using the temporal context, user preference of drinks in an airport can be very different from those at the vocation spots. Even in the same place, underlying reasons of items and users can affect on each other and drive user preferences latently. In this paper, we address the context-aware issue from a new perspective[1]. The approach designed here takes into the consideration that the product ratings are not only determined by personal factors but also by its coupled contextual information.

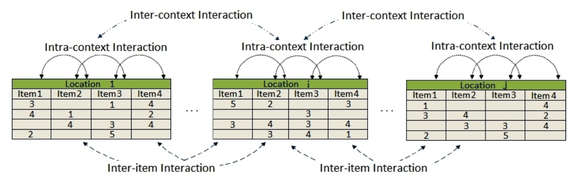


Figure 1: An illustration on contextual coupled similarity where context is "Location".

Coupled Collaborative Filtering

In our approach, coupled similarity computation is proposed in terms of inter-item, intra-context, and inter-context interactions (Fig.1). The intra-context captures the interactive relationships within a context, while the inter-item and the inter-context measure the relations among different contexts.

Inter-item Interaction

Definition 1 The Inter-item Interaction between contexts i and j is quantified as as an $L \times L$ matrix $M^{InterI}(i,j)$, in which the (p, q) entry $(1 \leq p, q \leq L)$ describes the correlation between each pair of item ratings $\langle r_i \rangle^p$ and $\langle r_j \rangle^q$:

$$M^{InterI}(i,j) = \begin{bmatrix} m_{11}^{InterI}(i,j) & m_{12}^{InterI}(i,j) & \cdots & m_{1L}^{InterI}(i,j) \\ m_{21}^{InterI}(i,j) & m_{22}^{InterI}(i,j) & \cdots & m_{2L}^{InterI}(i,j) \\ \vdots & \vdots & \ddots & \vdots \\ m_{L1}^{InterI}(i,j) & m_{L2}^{InterI}(i,j) & \cdots & m_{LL}^{InterI}(i,j) \end{bmatrix}$$

where $m_{pq}^{InterI}(i,j) = Cor(\langle r_i \rangle^p, \langle r_j \rangle^q)$ is the Pearson's correlation coefficient (Gan, Ma, and Wu 2007) between values $\langle r_i \rangle^p$ and $\langle r_j \rangle^q$, which are the ratings on items p and q across all users on contexts i and j respectively.

Intra-context Interaction

Definition 2 The Intra-context Interaction within a context i is represented as an $L \times L$ matrix $M^{IntraC}(i)$, in which the (p, q) entry describes the correlation between the values $\langle r_i \rangle^p$

[1]For more information about our approach and experiments, see http://janejiangccf.weebly.com/

and $\langle r_i \rangle^q$:

$$M^{IntraC}(i) = \begin{bmatrix} m_{11}^{IntraC}(i) & m_{12}^{IntraC}(i) & \cdots & m_{1L}^{IntraC}(i) \\ m_{21}^{IntraC}(i) & m_{22}^{IntraC}(i) & \cdots & m_{2L}^{IntraC}(i) \\ \vdots & \vdots & \ddots & \vdots \\ m_{L1}^{IntraC}(i) & m_{L2}^{IntraC}(i) & \cdots & m_{LL}^{IntraC}(i) \end{bmatrix}$$

where $m_{pq}^{IntraC}(i) = Cor(\langle r_i \rangle^p, \langle r_i \rangle^q)$ is the Pearson's correlation coefficient for ratings within context i between different items p and q.

Inter-context Interaction

Definition 3 The Inter-context Interaction calculates inter context correlation based on previous intra-context interaction, which aims to measure specific contribution of each intra-context interaction on different contexts:

$$M^{InterC}(i,j) = \begin{bmatrix} m_{11}^{InterC}(i,j) & m_{12}^{InterC}(i,j) & \cdots & m_{1L}^{InterC}(i,j) \\ m_{21}^{InterC}(i,j) & m_{22}^{InterC}(i,j) & \cdots & m_{2L}^{InterC}(i,j) \\ \vdots & \vdots & \ddots & \vdots \\ m_{L1}^{InterC}(i,j) & m_{L2}^{InterC}(i,j) & \cdots & m_{LL}^{InterC}(i,j) \end{bmatrix}$$

where $L \times L$ matrix $M^{InterC}(i,j)$ describes the Pearson's correlation between the two intra-context interactions of $M^{IntraC}(i)$ and $M^{IntraC}(j)$. For instance, $m_{pq}^{InterC}(i,j) = Cor(\langle m^{IntraC}(i) \rangle^p, \langle m^{IntraC}(j) \rangle^q)$ is the correlation coefficient for $m^{IntraC}(i), m^{IntraC}(j)$ between different items p and q.

Coupled Similarity Integrated-weight

Coupled Similarity Integrated-weight $w_{i,j,v}$ between two different contexts i and j for specific item v, integrating the inter-item and inter-context interactions of contextual information, is measured as follows.

$$w_{i,j,v} = \frac{\|M_v^{InterI}(i,j)\|_F + \lambda \|M_v^{InterC}(i,j)\|_F}{1+\lambda} \qquad (1)$$

where $\|M_v^{InterI}(i,j)\|_F = \sqrt{\sum_{k \in L} (m_{vk}^{InterI}(i,j))^2}$, reflecting the inter-item relationship between context i and j,
$\|M_v^{InterC}(i,j)\|_F = \sqrt{\sum_{k \in L} (m_{vk}^{InterC}(i,j))^2}$, reflecting the inter-context relationship between context i and j.

For Coupled Collaborative Filtering(CCF), Coupled Similarity is used to predict the contextual rating. Here we use the standard weighted average to predict the rating (Su and Khoshgoftaar 2009), P_{u,v,c_i}, for user u on item v in context c_i:

$$P_{u,v,c_i} = \frac{\sum_{c_j \in N} r_{u,v,c_j} w_{c_i,c_j,v}}{\sum_{c_j \in N} \mid w_{c_i,c_j,v} \mid} \qquad (2)$$

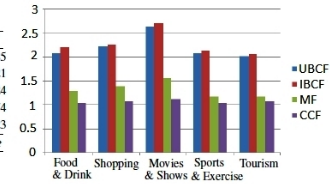
where the summations are over all other rated contexts $c_j \in N$ on item v by user u, $w_{c_i,c_j,v}$ is the weight between contexts c_i and c_j on item v, r_{u,v,c_j} is the rating for user u on item v in the context c_j.

Experiments

The experiments were conducted on a real-world dataset, which is a GPS location data recorded from from April 2007 to Oct. 2009 in the city of Beijing, China (Zheng et al. 2010). It covered a total length over 139,310 kilometers and extracted into 5 different types of activities, "*Food & Drink*", "*Shopping*", "*Movies & Shows*", "*Sports & Exercise*" and "*Tourism*" in the 168 locations for this study.

Model	*UBCF*	*IBCF*	*MF*	*CCF*
Food & Drink	2.50835	2.60468	1.71146	1.33885
Shopping	2.70816	2.75476	1.79297	1.42321
Movies & Shows	3.06439	3.15677	1.87627	1.61924
Sports & Exercise	2.47597	2.50778	1.46167	1.21474
Tourism	1.65684	2.46739	1.27661	1.03623
T-test	*0.0112*	*0.0001*	*0.0005*	*Base*

(a)



(b)

Figure 2: The results of all comparative models (a) RMSE of comparative models. (b) MAE of comparative models.

The most widely used evaluation metrics Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) (Su and Khoshgoftaar 2009) measure the rating prediction quality.

We set λ in Equation 2 to 1 to obtain an equally weighted average between inter-item and inter-context interactions. The comparative models in the experiments are UBCF*: Recommender based on user-based collaborative filtering method (Su and Khoshgoftaar 2009) (5 closest users as the neighborhood)*, IBCF*: Recommender based on item-based collaborative filtering method (Su and Khoshgoftaar 2009) (5 closest items as the neighborhood)*, and MF*: The most well-known MF method by minimizing the squared error by stochastic gradient descent (Koren, Bell, and Volinsky 2009).* To verify the significance of the performance improvements, we conducted paired *t*-tests between CCF and the other methods in comparison. The low *p*-values returned from the tests shown in the Fig.2(a) demonstrate the significant advantages of our method. Moreover, Fig.2(b) illustrates that CCF can better capture the contextual factors for prediction ratings. In terms of MAE, compared to UBCF, IBCF and MF models, our proposed archives at least 12% improvements over all testing cases.

Conclusions

In this paper, we propose a coupled collaborative filtering (CCF) approach to measure the relationships among users, items and contexts. Empirical results demonstrate the effectiveness of our approach. In future work we plan to apply it on other related fields such as risk-aware recommendation.

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